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Abnormal Diagnosis and Prediction Using Multi-Task Learning in Nuclear Power Plants

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1. Introduction

Recently, various studies [1-3] using artificial intelligence (AI) have been conducted in the nuclear industry to reduce the risk of operators and prevent accidents. Through these studies, technologies such as operator support system, accident diagnosis, and prediction of the remaining useful life of the components are being developed. In particular, research on abnormal states diagnosis is being actively conducted to support the operation procedure selection process that causes an increase in human error. However, in order to prevent accident aggravation and reactor trip, it is also necessary to provide future information on monitoring variables in addition to status diagnosis.

Accordingly, in this study, we propose abnormal diagnosis and prediction using a multi-task learning (MTL) method in abnormal states. Specifically, it performs the task of diagnosing abnormal scenarios and predicting the future values of monitoring variables through a single model. The prediction target variables were selected as the pressurizer (PRZ) water level and pressure, which are the main variables that check the integrity in the abnormal PRZ states. The MTL applied in this study is a method to improve learning efficiency and performance through a single model for multiple tasks. In other words, it aims to improve generalization performance for all tasks by utilizing the useful information contained in data from multiple tasks [4].

The applied data are numerical data acquired through a compact nuclear simulator (CNS), and data from six abnormal scenarios were used among many scenarios. The input variables were selected using symptom analysis and the correlation coefficient method. After then, the data were divided into diagnosis and prediction datasets. In this study, the MTL-based model developed to confirm the effectiveness of MTL was compared with each individual diagnosis and prediction model.

2. Methods for abnormal diagnosis and prediction

2.1 Multi-task learning

MTL is a method for jointly learning several related tasks inspired by the human learning ability [4]. That is, it is a method to improve generalization performance for all tasks by sharing characteristics of related tasks. Also, MTL performs model parameter reduction and efficient calculation by learning multi-tasks at the same time. MTL is generally divided into hard parameter sharing and soft parameter sharing structures [5]. Hard parameter sharing is a commonly used structure in MTL. It has a structure that extracts common features by sharing a hidden layer, and then learns to improve the performance of each task through an output layer for each task. The advantage of this structure is that the model improves generalization performance for all tasks, thus avoiding overfitting. Soft parameter sharing has its own layers for each task. Also, a penalty is applied so that the parameters of the layers have similar weight to reduce the difference between layers. Fig. 1 shows the two structures of parameter sharing in MTL. In this study, abnormal diagnosis and prediction were performed by applying MTL based on the hard parameter sharing structure.

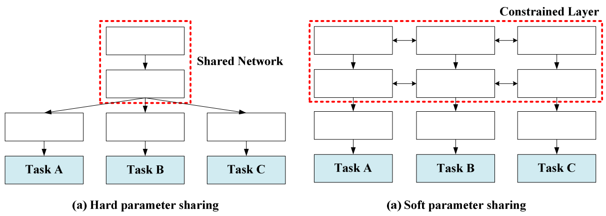

Fig. 1. Structure of parameter sharing in MTL

2.2 Architecture of multi-task learning model

The structure of the MTL model applied for abnormal diagnosis and prediction is shown in Figs. 2 and 3. The shared network consists of long short-term memory (LSTM) [6], a method specialized for time-series data. In the case of Fig. 2, an abnormal diagnosis and prediction results are output based on single input data (i.e., Input1). As mentioned in section 2.1, it is designed to improve the performance of abnormal diagnosis and prediction tasks by sharing information about each task through a shared network. In the case of Fig. 3, Input3 is added to the prediction network in order to further improve the performance of the prediction task after dividing Input1 into Input2 and Input3. Input2 consists of diagnosis variables and variables with high correlation coefficient values; Input3 consists of variables with low correlation coefficient values. That is, by adding Input3, the model was established to further improve the performance of the prediction task along with information sharing through the shared network. Finally, the tasks are as follows:

- Task 1: abnormal diagnosis
- Task 2: prediction of variable value after 30 steps

- Task 3: prediction of variable value after 60 steps
- Task 4: prediction of variable value after 90 steps

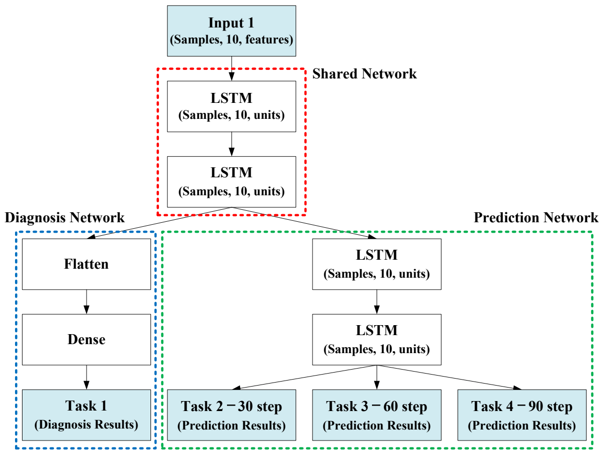

Fig. 2. Structure of MTL with single-input

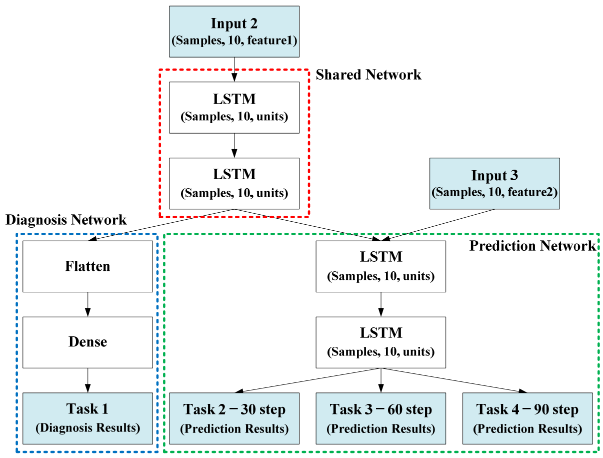

Fig. 3. Structure of MTL with multi-input

2.3 Optimization of multi-task learning model

In order to accurately perform abnormal diagnosis and prediction through the MTL model designed as shown in Figs. 2 and 3, the parameter optimization process is required. First, Adam was used as the optimizer function to optimize the model. Also, the model was trained by varying the LSTM units, batch size, and learning rate. The optimal model is selected when the total loss value was the lowest. The loss functions of abnormal diagnosis and prediction tasks are categorical cross entropy and mean squared error, respectively. The total loss is calculated as Eq. (1).

$$L_{total} = \sum_{i=1}^{t} w_i L_i \tag{1}$$

where w_i and L_i are weighted value and loss value for each task, respectively. And t is the number of tasks.

3. Data preprocessing

The used data are abnormal data acquired through the CNS. Table I shows the applied scenarios for MTL-based AI model development. After the data acquisition, data preprocessing is required for training the AI model. The process consists of input variable selection, data standardization, and transformation into a form of input data suitable for the AI method to be applied. In this study, the input variables were selected through the symptom analysis and Pearson correlation coefficient methods. The input variables consist of variables representing the scenario characteristics and variables related to the PRZ. After then, data standardization is performed based on the selected input variables. Data standardization is a method of transforming data into a normal distribution. Finally, standardized data is converted to the input data form of the LSTM.

Table I: Acquired abnormal scenarios

No.	Scenario name
1	Normal
2	PRZ pressure channel failure – high
3	PRZ water level channel failure – high
4	PRZ water level channel failure – low
5	PRZ power-operated relief valve opening
6	PRZ safety valve failure
7	PRZ spray valve failure - opening

4. Results of abnormal diagnosis and prediction

An abnormal diagnosis and prediction model was developed based on MTL using single and multi-inputs. The performance of the model developed based on MTL was evaluated through accuracy, root mean squared error (RMSE), and R-square (R^2). The accuracy is used to evaluate abnormal diagnosis task (i.e., Task 1). The higher the accuracy, the better the model performance. RMSE and R^2 are used to evaluate the variable state prediction tasks (i.e., Tasks 2-4). The lower the value of RMSE and the closer R^2 is to 1, the better the performance. RMSE and R^2 are calculated as in Eqs. (2) and (3).

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(\frac{y_k - \hat{y}_k}{y_{\max}} \times 100\%\right)^2} \tag{2}$$

$$R^2 = 1 - \frac{\sum_{k=1}^{N}(y_k - \hat{y}_k)^2}{\sum_{k=1}^{N}(y_k - \bar{y})^2} \tag{3}$$

where y_k and $\hat{y}_k$ are real and predicted values, respectively. $y_{\max}$ and $\bar{y}$ represents the maximum and mean values of variable, and N is the number of samples.

The performance comparison of the developed diagnosis and prediction model was performed with a single-task learning (STL) model. The STL model has a structure in which LSTM layers are sequentially stacked and uses the same model parameters as MTL model. And, the STL model used Input1 as input data (refer to Fig. 2).

Table II shows the diagnosis results from the MTL and STL models for training and test datasets. In the table, Model 1 and Model 2 are the same as the structure of Figs. 2 and 3, respectively. As for the diagnosis results, all models showed 100% accuracy in training dataset, but the STL model showed the highest accuracy in test dataset. Tables III and IV show the prediction performance of PRZ water level and pressure. In the case of Model 3, an individual model was developed for each task. In the prediction tasks, the MTL model shows better performance than the STL model; and among the MTL models, Model 2 that injected additional input data into the prediction task performed much better.

Table II: Diagnosis results through MTL and STL models

Structure		Accuracy	
		Train data	Test data
MTL	Model 1	100%	98.208%
	Model 2	100%	98.226%
STL	Model 3	100%	98.229%

Table III: Prediction performance of PRZ water level through MTL and STL models

Structure		Performance	Test data		
			Task 2	Task 3	Task 4
MTL	Model 1	RMSE (%)	0.6103	0.6255	0.7343
		R^2	0.9992	0.9992	0.9990
	Model 2	RMSE (%)	**0.4213**	**0.4008**	**0.3703**
		R^2	**0.9996**	**0.9997**	**0.9997**
STL	Model 3	RMSE (%)	1.3903	0.8039	1.529
		R^2	0.9959	0.9987	0.9956

Table IV: Prediction performance of PRZ pressure through MTL and STL models

Structure		Performance	Test data		
			Task 2	Task 3	Task 4
MTL	Model 1	RMSE (%)	0.6229	0.6252	0.7124
		R^2	0.9985	0.9985	0.9980
	Model 2	RMSE (%)	**0.1911**	**0.2222**	**0.2425**
		R^2	**0.9999**	**0.9998**	**0.9998**
STL	Model 3	RMSE (%)	0.8116	1.1730	4.8753
		R^2	0.9974	0.9946	0.9068

Although the developed MTL model showed little difference in performance from the STL in the diagnosis task, the RMSE decreased by a maximum reduction of 4.6% and the R^2 value was close to 1 in the prediction tasks. Figs. 4 and 5 show the prediction results through the Model 2.

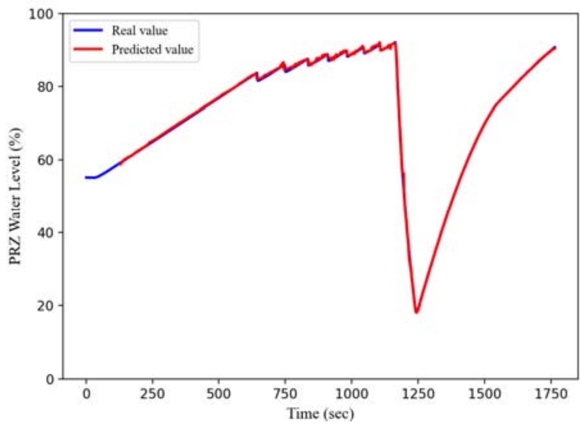

Fig. 4. Prediction results of PRZ water level for Task 4

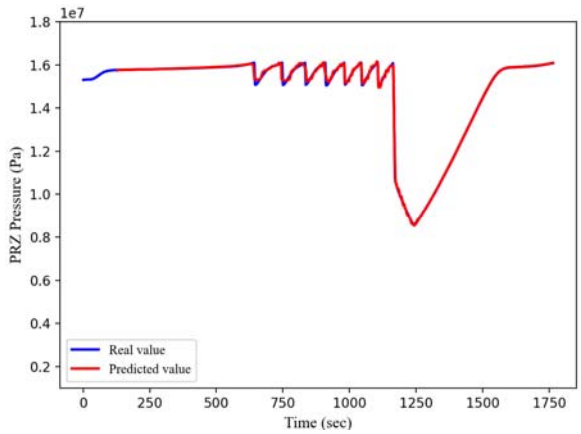

Fig. 5. Prediction results of PRZ pressure for Task 4

5. Conclusions

In this study, abnormal diagnosis and prediction were performed using MTL for the purpose of developing a technology to reduce human error of operators during abnormal states. The diagnosis task is to classify seven scenarios, including normal. The prediction tasks are to predict the values after 30, 60, and 90 steps of the PRZ water level and pressure. The advantage of the MTL method is to improve the performance of all tasks over a shared network. In addition, two structures based on MTL method were proposed in this study. The proposed MTL models showed better overall performance than the STL model. Also, the accuracy and prediction performance of Model 2, which adds input data to the prediction task, were better than Model 1.

Since only the PRZ water level and pressure were predicted among the main monitoring variables to be checked during abnormal states in nuclear power plants, it is necessary to provide information on more variables in the future. Also, only seven scenarios in the study were diagnosed, but it is necessary to diagnose all abnormal scenarios. If an improved MTL-based abnormal diagnosis and prediction model is developed, it is expected that human errors can be reduced by providing the operator with diagnosis and state information on monitoring variables.

Acknowledgment

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